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Outline a fault diagnosis system for a large-scale board machine

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Abstract Global competition forces process industries to continuously optimize plant operation. One of the latest trends for efficiency and plant availability improvement is to set up fault diagnosis and maintenance systems for online industrial use. This paper presents a methodology for developing industrial fault detection and diagnosis (FDD) systems. Since model or data-based diagnosis of all components cannot be achieved online on a large-scale basis, the focus must be narrowed down to the most likely faulty components responsible for abnormal process behavior. One of the key elements here is fault analysis. The paper describes and briefly discusses also other development phases, process decomposition, and the selection of FDD methods. The paper ends with an FDD case study of a large-scale industrial board machine including a description of the fault analysis and FDD algorithms for the resulting focus areas. Finally, the testing and validation results are presented and discussed.

Keywords: Fault monitoring, fault diagnosis, large-scale systems, paper industry, industrial application, board machine

1 Introduction

Increased global competition, increased product quality requirements, and safety and environmental regulations have forced the process industry to continuously optimize the efficiency and profitability of its plants. Better profitability can generally be achieved through process optimization, by cutting costs, and by reducing down-time caused by unplanned and planned shutdowns. Optimization can be further enhanced by focusing on preventing off-spec production caused by process disturbances and faults. To this end, there has been an increasing interest in process monitoring and fault diagnosis methods in the process industry. Reviews these methods have been published e.g. by Isermann (2011).

Process knowledge has always played a key role in development of fault detection and diagnosis (FDD) systems for process industries. As a result, the FDD methods have been classified in the following three categories based on the type of information they use: quantitative-model-based, qualitative-model-based, and process-history-based methods (Venkatasubramanian et al 2003a).

The quantitative-model-based methods include observers, parity relations, Kalman filters, and parameter estimation (see e.g. Ding 2008). However, the applicability of the methods is limited to linear processes. Qualitative-methods are used when there is no deep understanding of the process and when precise numerical models are not available (Lo et al., 2004). Qualitative models are less prone to modelling errors than the quantitative models. The drawback of the qualitative modelling is the occasional generation of spurious results. Qualitative models are most suitable for finding the root causes of faults in very complex or large processes. The most common model-based qualitative methods are signed digraphs, fault trees, and qualitative physics (Venkatasubramanian et al 2003b.)

The third group of methods is the history-based methods, which utilize the knowledge extracted from the history data in a qualitative or quantitative way. Rule-base expert systems and qualitative trend analysis are two of the most important methods based on qualitative historical data (Venkatasubramanian et al 2003c). The quantitative model based methods also include artificial neural networks and statistical methods. Depending on the type of problem, these methods are applied using a classification or a regression scheme. Moreover, the benefit of easy implementation is reflected by a large number of industrial applications reported, e.g. by Sourander et al (2008), Jämsä-Jounela (2011), and Kettunen and Jämsä-Jounela (2011).

The methods in each category have their strengths and weaknesses, and it has been stated that no single method meets the requirements for a good diagnostic system (Dash and Venkatasubramanian 2000). To overcome the disadvantages, hybrid approaches have been proposed that either combine the results of different methods or combine incomplete process information available from methods different categories (e.g. Chung et al 1994; Lee and Yoon 2001; Vedam and Venkatasubramanian, 1999). These methods are generally sufficient for unit processes and small-sized processes, but they usually become inefficient in large-scale processes. Therefore, strategies based on process decomposition have been developed to tackle the challenges of large-scale systems. A process can be decomposed in a structural or functional manner by utilizing either a top-down or a bottom-up strategy.

For example, Prasad et al (1998) have proposed a decomposition methodology based on the structure of a chemical plant. However, there are no well-defined criteria to evaluate the optimality of these decomposition schemes.

Commercial software products play an important role in managing industrial processes by facilitating information gathering and operational control. Due to the increased demand by industry, the special software products for process monitoring and fault diagnosis have been also developed. One of the earliest ones is G2 (Gensym Corporation, 1997a, b), which is used in many successful industrial applications (e.g. Lee and Yoon 2001; Mjaavatten and Foss, 1997). Moreover, the AEGIS (Abnormal Event Guidance and Information System) software product has been introduced by Honeywell Inc. Lists of its successful applications can be found in Venkatasubramanian (2010), Honeywell Inc. (2005) and Morison et al (2006). The software EFDD (Early fault and disturbance detection) has been developed by ABB, Statoil and academic institutions (ABB AS n.d.). The methods incorporated in EFDD are PCA and plant-wide disturbance detection methods presented in Thornhill and Horch (2007). A commercial product of data gathering and analysis for water treatment applications is presented in Edthofer et al (2010). This product has been well received in the water industry, and some applications have been reported by Langergraber et al (2004) and (2006). The AHEAD toolkit has been developed by Barric Gold and SGS Advanced Systems (SGS Group) and it was introduced by Power et al (2009). The objective of AHEAD is optimal utilization of assets and efficiency using KPIs (key performance indexes), neural networks, PCA, PLS and causal digraphs. It has been successfully applied in a uranium solvent extraction circuit. KPS is a product of the XpertRule Company that performs three main tasks: plant data analysis, performance monitoring, and equipment control and optimization. It has applications in different fields, such as oil & gas industry and power generation. Based on this survey a comprehensive software tool for FDD in large-scale industrial systems is still missing and is under further research and development.

The comprehensive literature research of FDD methods and their applications, as well as many commercial FDD systems thus successfully address the small-scale FDD problems in the industry. This paper proposes a methodology for FDD system development for a large-scale industrial system, where fault analysis and process decomposition play key roles. The methodology has also been successfully applied to the large-scale board machine. Novel FDD algorithms for the most critical faults of the board machine are developed and presented in the paper. Finally, the testing results with industrial data are presented and discussed.

This paper is organized as follows. First, a methodology for industrial FDD system development is presented in Section 2. The case process, an industrial large-scale board machine, is described in Section 3. Next, fault analysis of the board machine is described in Section 4. Furthermore, the selection and development of FDD algorithms, including a novel algorithm for detecting faults in the drying section of the board machine, are presented and discussed in Section 5. Section 6 concludes the fault analysis and the FDD results.

2 Methodology for FDD system development

Development of an FDD strategy for a large-scale system includes the following five main phases: process decomposition, fault analysis, definition of the user requirements and system specifications, construction of a diagnostic technique for each subsystem, and the combination of the diagnostic results of subsystems to determine the fault. The final phase of the methodology consists of validation of algorithms and their industrial implementation. (Jämsä-Jounela 2011).

2.1 Process Decomposition

Complex industrial systems are characterized both by the intrinsic difficulty of their design and by the large number of subsystems and the different kinds of technology involved. A centralized approach has in most cases proved to be insufficient for the investigation of industrial large-scale processes. Process decomposition has therefore often been selected as a prior step of developing a fault diagnosis system for these processes. Use of a decomposition scheme based on the process topology is well accepted and widespread in industry (Prasad et al 1998). However, it needs to have the following desired properties: enhancement of fault localization through minimization of interactions among subsystems, improved resolution through maximization of interactions within each subsystem, and a compromise between the number and sizes of subsystems. The best decomposition methodology thus follows the general structure of chemical processes and involves a combination of the structural and functional decompositions.

At the highest level of the hierarchy, the objectives are selected, for example, production of a particular product and/or product quality and safety. Next, the primary process systems – including feed, reactions, and separation (or combinations) – are selected, and the relevant part of the process is investigated accordingly. Each primary process system is then decomposed into subsystems by considering their interactions. Control loops are best placed in the subsystems and strongly interacting control loops are grouped together. Furthermore, closely related process systems are coupled together, e.g. the reactor and the cooling jacket around it. The recycling streams are also considered since they interconnect the process units. Finally, the process unit and/or devices/instruments are determined as nodes under each subsystem. Plant topology, PI-diagrams, and expert knowledge are used for specifications.

2.2 Fault analysis

The first aim of fault analysis is to find out the main reasons for production losses and thus the main focus areas for FDD system development. Fault analysis is carried out as data analysis, but it should be supported by interviews of the plant personnel. The data sources are long-term maintenance and production data as well as process measurement and alarm history data.

First shutdowns, both planned and unplanned, are categorized. Next the unplanned shutdowns are further categorized into maintenance and operational ones. The operational data of the unplanned shutdowns is the main data source for the development of FDD algorithms.

The second aim of fault analysis is to study the most common faults in the process. The objective is to discover the location and causes of the faults, and to identify the corresponding faulty devices. The fault types are categorized e.g. as follows: malfunction, leakage, clogging or jamming, vibration, fouling, breakage, etc. The fault causes are similarly classified: wearing, component failure, impurities or moisture, misoperation, etc. These fault types and causes are further placed to concern specific devices using the decomposition results or root cause analysis.

2.3 User requirements and system specifications, confirmation of FDD focus areas

Development of an FDD application for an industrial process requires background information concerning the aims of the FDD, expectations of the plant personnel and restrictions of the technical platforms, for instance. This information is collected through interviews of the plant operating personnel. In order to cover as many perspectives of as many subjects as possible, it is recommended to interview personnel working in different operational sectors, such as operators, engineers, maintenance experts, and management. Based on the fault analysis results and the feedback from the operating personnel, the key areas of FDD developments are determined.

2.4 Selection of FDD methods

Selection of the most suitable methods for a specific FDD problem depends on many factors, e.g. intended use of the method, the process and its dynamics, and especially the faults and their characteristics. Most of the FDD methods in the process industries are implemented as advanced supervision methods. Surveys of the analytical fault-detection methods and the fault diagnosis methods are presented e.g. by Isermann (2011). He classifies detection and diagnosis as separate tasks. Detection methods are classified according to the type of elements used to detect an abnormal state, while diagnosis methods are classified according to the type of the decision methodology used.

The fault detection method classification is based on signals employed by the methods. Detection performed using single signals includes methods like limit and trend checking. Detection performed using multiple signals consists of methods that make use of multivariate analysis. The detection methods, which use models, can be grouped together with the single signal methods, if the signal behaviour is the modelled element, or with multiple signals, if the process is being modelled.

There are two main categories for classification of fault diagnosis methods: The methods in the first category use classifiers to evaluate the symptoms in order to achieve diagnosis decision. Classification methods are used in absence of any structural information about the process related to the symptoms and the faults. Pattern recognition, statistical classification approximation methods, density-based methods, and artificial intelligence methods belong to these methods. The second category contains inference methods like binary reasoning and approximate reasoning.

2.5 Implementation and testing

The FDD algorithms are tested both in offline and online. Offline testing is done in the simulation environment utilizing the collected plant data: one data set for training, one for testing and one for validation. A recommendation for online testing is to embed the FDD algorithms in the different process control hierarchy levels and to test the algorithms in the plant automation facilities using online process operation data.

3 Description of the process and its control strategy, process decomposition

The board-making process begins with the preparation of raw materials in the stock-preparation section. Different types of pulp are refined and blended according to a specific recipe in order to achieve the desired composition and properties for the board grade to be produced. The consistency of the stock is controlled by the addition of dilution water.

The blended stock passes from the stock preparation to the short circulation. First, the stock is diluted in the wire pit to the correct consistency for web formation. Next, the diluted stock is cleaned and screened, after which it passes to the head box, from where it is sprayed onto the wire in order to form a solid board web.

The excess water is first drained through the wire and later by pressing the board web between rolls in the press section. The remaining water is evaporated in the drying section using steam-heated drying cylinders. After the drying, the board is calendered in two phases in order to achieve the desired surface properties. An overview of the board machine process is presented in Figure 1. Details of the process can be found in (Cheng et al 2011).

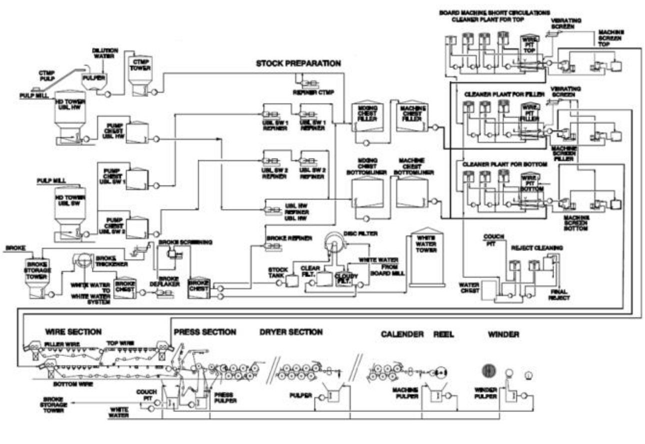

Fig. 1 Overview of the Board machine 4 process (modified from (Sundholm 2000))

The main control system of the board machine is the quality control system (QCS), which represents the highest level in the control hierarchy. By utilizing model-predictive control schemes, it controls the main quality variables, basis weight moisture, and thickness, in the machine direction and in the cross direction. The quality variables are measured after the calender section with a measurement scanner that traverses constantly across the web. The calculated control actions are delivered as setpoints to lower level controllers.

In the machine direction, the stock flow controller setpoints are adjusted according to the basis weight controller, while the steam pressure setpoints in the drying section are governed by the moisture controller. In the cross direction, the QCS system controls special actuators that adjust the profiles of the quality variables. The basis weight profile is controlled by the dilution water in the middle layer headbox, while the moisture profile is controlled with a steam box located before the press section and with a moisturizing device in the drying section. The thickness profile is controlled at the second calender.

These controls are supported by a large number of basic controls that adjust pressures, flows, level, etc. around the board machine.

To develop an FDD system application for large-scale industrial plants, a decomposition methodology based on the structure of the factory is recommended (Prasad et al 1998). In this case study, the board machine has been first decomposed into nine sections (see Figure 1): stock preparation, short circulation, broke processing, wire section, press section, drying section, calender section, reeling, and QCS. Next, the sections are decomposed into equipment and field instruments. As an example, the decomposition of the board machine focusing on the drying section is shown in Figure 2.

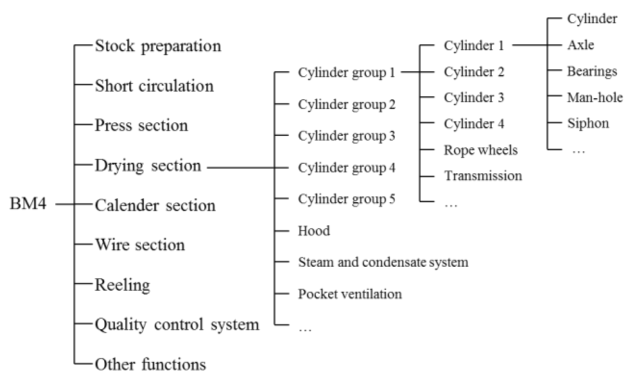

Fig. 2 Decomposition of the board machine focusing on the drying section

4 Fault analysis of the BM4

In the year 2009, the automation system of the board machine at Imatra Mills was updated and the 1st calendar was renewed. Due to these major updates, the board machine was selected as a good candidate for the FDD project. The fault analysis aimed at finding the main focus areas for FDD system development. For this purpose, the long-term production and maintenance data from the year 2010 were collected for this study. (Laavi et al 2011).

4.1 Analysis of the Production Losses

Web breaks and shutdowns were studied as a first phase of the fault analysis. These events caused interruptions in board production for one third of the analyzed time interval during the year 2010. Both unplanned and planned shutdowns resulted in a total production interruption of three months which was significantly longer than the additional two-week interruption caused by the web breaks. Additionally, the statistics showed that the web breaks were nearly always due to operational reasons whereas unplanned shutdowns can also be caused by maintenance needs. The operational causes consisted mainly of process disturbances whereas maintenance faults were, for example, caused by mechanical failures. The distribution of the production time, the web breaks, and the shutdowns of the test case are presented in Table 1.

The studied year was exceptional in terms of normal production efficiency as it was the first complete production year after employment of the new equipment. The plant experts stated that the reported data are typical numbers for this stage of implementation of the new device. Start-up related problems usually last three years.

Table 1 Distribution of production time, web breaks, and shutdowns, and the cause distribution of the web breaks and unplanned shutdowns

Event	**Duration**		**Cause**		
	h	*%*		*h*	*%*
Web break	13.2	5	Maintenance	0.6	4
			Operational	12.5	95
			Unspecified	0.2	1
Unplanned shutdowns	42.7	15	Maintenance	21.3	50
			Operational	20.4	48
			Unspecified	1.0	2
Planned shutdowns	49.9	16			
Normal production	186.1	64			
Total	**288.9**				

In the case of the production of special products, the sensitivity of each product to web breaks and shutdowns has to be carefully checked. The effect of the produced board grade on the frequency of the web breaks and shutdowns was next studied for two types of board, called A and B here. The types were categorized into three or four board grade blocks according to whether the board basis weight was low, medium, or high.

The statistics show that board grade blocks with the lowest basis weight have an increased risk for web breaks (Table 2). Board grade blocks with the highest basis weight are also susceptible to web breaks, as seen in the case of the board type B. This type of dependency on the board grade block basis weight did not appear in the case of shutdowns, as can be seen in Table 2. The analysis of the shutdowns reveals that the production of the grades in the block B (high) also suffers from repetitive shutdowns.

Table 2 The statistics of the web breaks and shutdowns by grade blocks of board types A and B of various basis weights.

Grade block	Web Breaks		
	Production time (h)	Number of breaks	Percentage of production time loss (%)
A (low)	1073	87	6
A (mid-low)	2365	365	4
A (mid-high)	269	36	5
A (high)	199	10	3
B (low)	360	30	6
B (mid)	813	41	4
B (high)	91	8	10

Grade block	Shutdowns		
	Production time (h)	Number of shutdowns	Percentage of production time loss (%)
A (low)	1073	42	17
A (mid-low)	2365	172	21
A (mid-high)	269	9	15
A (high)	199	3	17
B (low)	360	11	14
B (mid)	813	22	13
B (high)	91	6	31

The results of the analysis of the production losses suggest that the different operation conditions should be considered when developing FDD systems for a board machine focusing development only on the specific board grades in question, for instance.

4.2 Distribution of Faults by Fault Types, Process Sections, and Devices

The aim of the fault statistics was also to identify the most typical fault types, the faultiest unit processes, and the devices connected with the faults.

In the study of typical fault types, malfunctions were reported as the most common fault type. This includes the problems caused by devices that function but in an incorrect way. As can be seen in Figure 3, other significant fault types were leakages and other damages, which produced 10 % of all faults. Clogging and jamming or loosening and disengagement presented every tenth fault. Vibration alone produced almost 5 % of the faults.

To study the fault distribution by unit processes, the results of the decomposition of the board machine were used. Among the first eight sections, the faults were distributed quite evenly, but QCS had twice as many faults as the other sections, as shown in Figure 4.

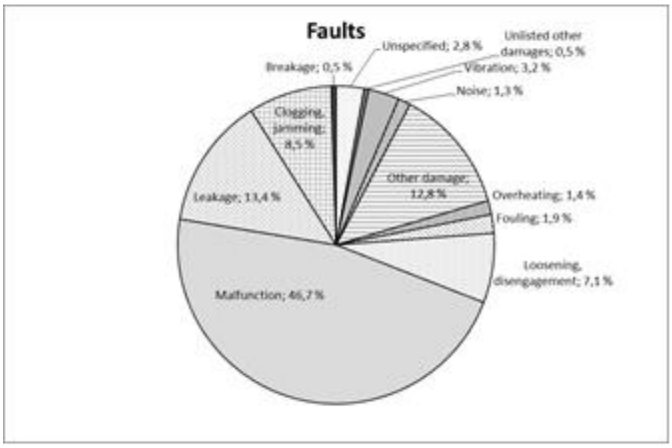

Fig. 3 Distribution of faults by the fault type

The faults that could not be assigned to only one of the unit processes were put into the category named Other functions. These include, among others, faults located in the ventilation of the machine hall and other faults in the supporting facilities of the plant.

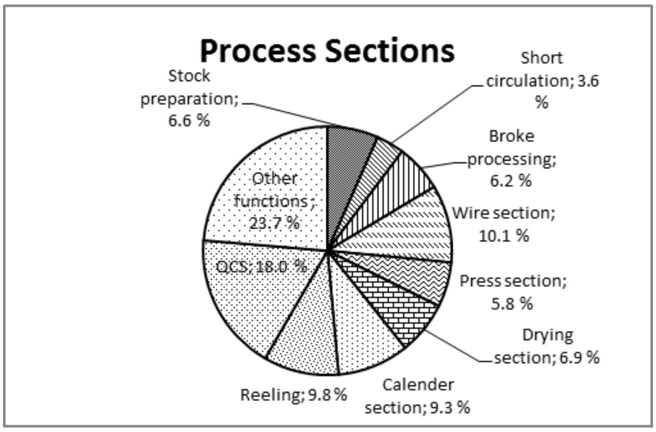

Fig. 4 Distribution of faults by the process sections

Next, the main fault types and devices were identified within the specific process sections. The QCS faults were however separately studied. The devices of the process units and their main faults are listed in Table 3. As can be seen in the table, process control devices caused the majority of the faults. In addition, valves were typical sources of malfunctions and leakages. Well-controlled drying is vital in board making, but the drying section suffers most from various leakages as can be seen in Table 4. Furthermore, the results indicate that problems in operation of valves cause every fifth fault. Leakages of pumps and pipes are also highlighted and recommended as targets of further FDD analysis.

Table 3 Classification of the main process devices and their main fault types.

Fault type	Percentage of all faults	Device
Malfunction	39.3 %	Actuators* Automations* Control systems* Positioners* Sensors* Transmitters* Valves Pumps Drives Drying cylinders Hydraulic devices
Leakage	15.5 %	Valves Pumps Pipes Hydraulic devices Sensors* Rolls Heat exchangers Tanks
Vibration	4.1 %	Roll

* Process control devices

4.2.1 QCS Fault Analysis

The QCS faults were analysed separately due to their crucial importance to the board making process. Table 5 lists the causes of all faults occurred in QCS. Furthermore, the table compares each cause's share of the typical QCS fault categories i.e., malfunctions, sensor malfunctions, and actuator malfunctions.

Table 5 Causes of all QCS faults, sorted by malfunctions, sensor malfunctions, and actuator malfunctions.

All causes		Mal-functions	Sensor mal-functions	Actuator mal-functions
Component failure	1.8 %	1.1 %	1.6 %	0.0 %
Corrosion/ oxidation	0.9 %	1.1 %	0.0 %	9.1 %
Exceptional conditions	1.8 %	2.1 %	1.6 %	9.1 %
Impurities, moisture	38.6 %	46.8 %	69.4 %	9.1 %
Misoperation	6.1 %	7.4 %	0.0 %	9.1 %
Normal wear	7.9 %	8.5 %	8.1 %	18.2 %
Other failure	3.5 %	3.2 %	1.6 %	0.0 %
Program fault	5.3 %	6.4 %	0.0 %	0.0 %
Safety switch	2.6 %	3.2 %	0.0 %	9.1 %
Unknown/ unspecified	31.6 %	20.2 %	17.7 %	36.4 %
Total	**100.0 %**	**100.0 %**	**100.0 %**	**100.0 %**

Table 4 The fault types by device in the drying section of the board machine. The focus areas of FDD development in this section are highlighted, other remarkable fault sources are bordered with dashed line

	DRYING SECTION	**Fault type**						**Total**
		Leakage	Loosening, disengagement	Malfunction	Noise	Other damage	Overheating	
Device	Drive	-	-	-	-	-	2.3 %	**2.3 %**
	Drying cylinder	-	6.8 %	4.5 %	-	2.3 %	-	**13.6 %**
	Gear and transmission	4.5 %	-	-	-	2.3 %	-	**6.8 %**
	Heat exchanger	2.3 %	-	-	-	-	-	**2.3 %**
	Mechanical	-	-	2.3 %	-	4.5 %	-	**6.8 %**
	Other mechanical device	-	-	4.5 %	2.3 %	-	-	**6.8 %**
	Pipe	9.1 %	-	-	-	-	-	**9.1 %**
	Positioner	-	-	9.1 %	-	-	-	**9.1 %**
	Pressure device	2.3 %	-	-	-	-	-	**2.3 %**
	Pump	11.4 %	-	-	-	6.8 %	2.3 %	**20.5 %**
	Roll	6.8 %	2.3 %	-	-	2.3 %	-	**11.4 %**
	Valve	2.3 %	-	6.8 %	-	-	-	**9.1 %**
	Total	**38.6 %**	**9.1 %**	**27.3 %**	**2.3 %**	**18.2 %**	**4.5 %**	**100.0 %**

4.3 Recommendations for Main Focus Areas of FDD Development

As a result of the fault analysis, the following areas were identified as the main focus areas for FDD development: QCS (board thickness measurements), the drying section (clogging, jamming, and leakages of valves; condensate problems), valves (malfunctions and leakages), and consistency sensor (malfunctions).

At the highest process control and monitoring level, FDD development should focus on the QCS due to its high share of the faults and its substantial importance to the board making process. Especially the faults in the measurements of board thickness need to be further studied.

At the unit process level, FDD development should focus on the drying section, which plays a key role due to its importance and strong influence on the other sections of the process. Especially clogging, jamming, and leakages of valves, and the condensate problems were selected as good candidates for FDD development.

At the lowest level of control hierarchy, malfunctions and leakages were selected as focus areas for FDD development. In addition, the consistency sensor, whose proper functioning is crucial to obtain the right board quality, is another candidate for FDD development.

5 Distributed FDD system development

The distributed FDD system for the board machine consists of a process monitoring module for thickness sensor fouling at the QCS level, a novel model-based FDD algorithm for leakages and blockages in the drying section, and detection of valve stiction and consistency sensor malfunction detection at the basic control level.

5.1 Supervisory control level (QCS) - SOM for thickness sensor fouling

A monitoring scheme utilizing self-organized maps (SOM) (e.g. Kohonen, 2001) was selected for predicting thickness sensor fouling at the process monitoring level. The development of the scheme included the selection of variables, the training of the SOM, and the monitoring tests using industrial data.

A monitoring scheme utilizing self-organized maps (SOM) (e.g. Kohonen (2001)) was selected for predicting thickness sensor fouling at the process monitoring level. The development of the scheme included the selection of variables, the training of the SOM, and the monitoring tests using industrial data. SOM is a type of a neural network that generates a low-dimensional representation, called a map, of the high-dimensional input space using unsupervised learning. A SOM consists of number of nodes described with a d-dimensional weight vector $\boldsymbol{w}_i = [w_1 w_2 \dots w_d]$.

The SOM is trained by adapting the weights of the nodes to match the input data. Training consists of the search of the closest map units, called the best-matching units (BMU), of the data samples and then the update of the weight vector l of the BMU and its neighbouring nodes. A BMU c is determined for a data sample $\mathbf{x} \in R^{\boldsymbol{d}}$ as follows:

$$\|\mathbf{x}-\mathbf{w}_{\mathrm{c}}\| = \min_i \|\mathbf{x}-\mathbf{w_i}\|, \quad i = 1, 2, \dots, m \qquad (1)$$

where $\|\cdot\|$ is Euclidean distance and m is the number of map nodes. The weight vector of the BMU and the neighbouring nodes are updated according to an update rule:

$$\mathbf{w}_{\mathrm{i}}(t+1) = \mathbf{w_i}(t) + \alpha(t) h_{ci}(t)[\mathbf{x}(t) - \mathbf{w_i}(t)], \qquad (2)$$

where t denotes time, $h_{ci}(t)$ is the neighbourhood kernel around the BMU and $\alpha(t)$ is the learning rate. In the batch training procedure the BMUs are calculated first for the whole data set, and then the weights are updated at once as follows:

$$\mathbf{w}_i(t+1) = \frac{\sum_{j=1}^{m} h_{ij}(t) s_j(t)}{\sum_{j=1}^{m} n_{V_j}(t) h_{ij}(t)}, \qquad s_i(t) = \sum_{j=1}^{n_{V_i}} \mathbf{x}_j, \qquad (3)$$

where n_{V_i} is the number of samples in the Voronoi set of the node i.

The list of variables for SOM monitoring consisted of thickness control error and its filtered derivative, temperature of the 1st calendar, zero-pressure level of the secondary hood, hood ventilation air temperature and some flows related to the chemicals used in the board production, see Table 6.

Table 6 Variable list for SOM-based monitoring

#	Tag	Description
1	F	Thickness measurement – thickness setpoint
2	DF	Filtered derivative of F
3	534TCZ_151	1st calender thermo roll temperature
4	PC0452	Zero-pressure level of the secondary hood
5	TI0451_7	Hood ventilation air temperature 7
6	FC0123	Wet strength size flow
7	FC0126	Starch flow
8	FC0202	Neutral size flow
9	FC0206	Retention starch flow
10	FC0242	Retention agent flow

Next, a SOM was trained using the variables listed in Table 7 and a fault indicator variable was developed based on the maintenance records to indicate process conditions in which the thickness sensor had given faulty readings. The monitoring tests were carried out by providing the SOM with a new data set containing normal operation data and faulty data.

The monitoring results of the SOM are presented in Figure 5, in which the estimated process state is compared with the value of the fault indicator. To reduce noise and false alarms, the estimated state has been filtered using a moving average filter with a window length of 5 samples

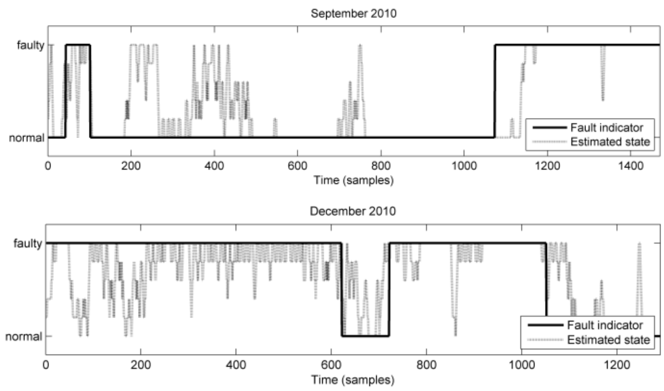

Fig. 5 Monitoring results using SOM

It can be confirmed from the figure that the SOM gives a rather good estimate of the actual process condition. In the September data (upper panel), the SOM can detect the faulty periods at the beginning of the month as well as after t = 1100. However, the process state is falsely estimated to be faulty after t = 200 and around t = 400. In the December data (lower panel), the process state is estimated satisfactorily during the first 600 samples except minor fluctuations in the estimation around t = 100 and t = 200. The non-faulty period after t = 600 is estimated successfully as well as the period in the end of the month. Table 7 summarizes the performance of the SOM by showing the rates of correctly estimated states, falsely estimated states and uncertain states.

Table 7 Results of the monitoring tests using SOM

	September	December
Rate of correct process states	78.0%	72.9%
Rate of false process states	11.9%	9.7%
Rate of uncertain process states	10.1%	17.4%

Based on the monitoring tests, the SOM is able to estimate the state of the process correctly in over 70% of time. The rate of falsely estimated states is rather low, approximately 10% on average. The perceived errors may result from the fault indicator, which has been developed based on the dates of the fault reports and therefore it might not be exactly aligned with actual fouling. Further development is however needed to address the chemical phenomena involved in fouling and the varying conditions of the process, for instance. The detailed description of the case study can be found in Tikkala and Jämsä-Jounela (2012).

5.2 Process unit level - FDD for the drying section

A novel FDD approach was proposed to detect and diagnose leakages and blockages in the valves and pipes of the drying section's steam-condensate system. The algorithm identifies a number of static nonlinear parity equations based on mass balances from the process data of the drying section and then utilizes the residuals of these equations for fault detection and diagnosis tasks. The changes in the residuals are detected using the cumulative sum (CUSUM) method and diagnosis is performed utilizing the structured residuals approach. To this end, an incidence matrix describing the faults vs. the residuals was developed. The model equations were defined to be of the following form:

$$\sum_{i=1}^{k} a_i x_i + \sum_{i=1}^{l} F_i^1(x_i^1) + \sum_{i=1}^{m} F_i^2(x_i^2, y_i^2) + \sum_{i=1}^{n} F_i^3(x_i^3, y_i^3, z_i^3) = 0, \qquad (4)$$

where variables *x*, *y* and *z* are process or computed variables, *k* is the number of linear terms involved in the equation with coefficients a_i, and *l*, *m* and *n* are the numbers of nonlinear fucntions with one, two and three arguments, respectively. F^1, F^2 and F^3 were defined using the following parameterization:

$$F^1(x) = \sum_{i=1,\dots,p} b_i g_i^x(x), \qquad (5)$$

$$F^2(x,y) = \sum_{i=1,\dots,p} \sum_{j=1,\dots,q} b_{i,j} g_i^x(x) g_j^y(y) \qquad (6)$$

$$F^3(x,y,z) = \sum_{i=1,\dots,p} \sum_{j=1,\dots,q} \sum_{k=1,\dots,r} b_{i,j,k} g_i^x(x)\, g_j^y(y) g_k^z(z) \qquad (7)$$

where b_i, $b_{i,j}$ and $b_{i,j,k}$ are the coefficients of the nonlinear functions, and *p*, *q* and *r* are the number of the basis functions g_i^x, g_j^y and g_k^z related to process variables *x*, *y* and *z*, respectively. The basis functions can be selected in many ways, for example a set of piece-wise linear basis functions as in this case study.

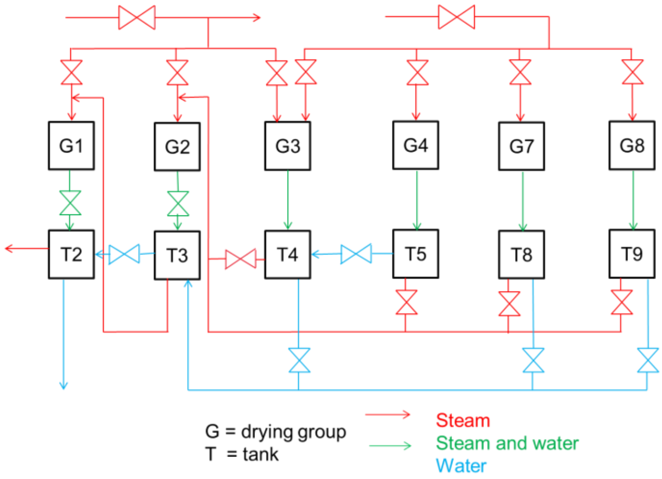

Fig. 6 Simplified scheme of the steam-condensate system

A simplified scheme of the steam-condensate system is presented in Figure 6. Based on this structure, the mass balance parity equations were developed and identified using the process data for the following drying section flows and units : the 10 bar feed steam flow, the 5 bar feed steam flow, the steam group 8, the steam group 7, the steam group 4 and the steam group 3. The results of the training and validation of the parity equations are presented in table 8.

Table 8 Summary of the developed parity equations

Parity equation	Training data		Validation data	
	R^2 (%)	Std (l/s)	R^2 (%)	Std (l/s)
10 bar steam feed flow	99.5	0.116	95.9	0.152
5 bar feed steam flow	91.9	0.167	-	-
Steam group 8	94.1	0.056	91.4	0.077
Steam group 7	91.2	0.046	93.6	0.046
Steam group 4	95.0	0.090	95.6	0.092
Steam group 3	96.9	0.133	-	-

The testing and validation results were good. The standard deviations of the residuals for the validation data were observed to be slightly higher (up to 50% higher) than those for the training data. This effect can be due to many factors, such as operating at the process conditions unexplored by the training data or frequent changes of the setpoints.

Taking into account the aforementioned factors, the minimum detectable change parameter of CUSUM was selected to be double the standard deviation of the residual obtained at the training data. The results of CUSUM tests are presented in Figure 7.

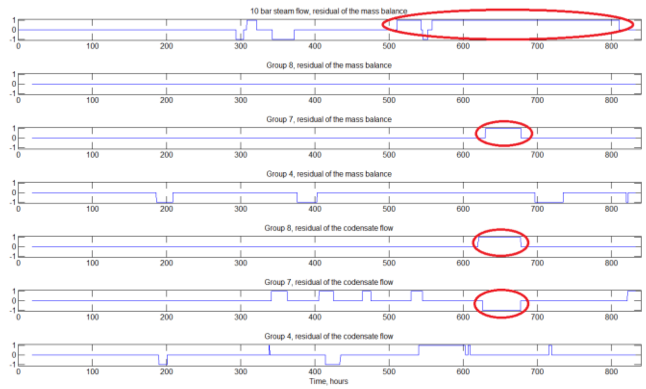

Fig. 7 Results of the CUSUM tests

Figure 7 shows that a fault was detected in the parity equation for the 10 bar feed steam flow: at hour 512 the residual became stably positive, while the residuals in the steam groups remained undisturbed. The fault is continuous almost until the end of the validation data (hour 812). According to the incidence matrix, the measurement of the 10 bar feed steam flow can be faulty. Correct detection and diagnosis was confirmed by a corresponding maintenance record which described a faulty measurement of 10 bar steam during that period.

A second fault was discovered between hours 621 and 678. During almost the same time, the mass balance for the steam group 7 became positive and the parity equations for the heat exchange in the steam groups 7 and 8 were disturbed. Though the incidence matrix did not provide any possible reasons for the fault, it is obviously located in the drying group 5 (which combines the steam groups 7 and 8). In the maintenance data, there were reported leakages in the drying group 5 during that time, which confirms the result.

This case study is described and presented in detail in Zakharov (2011).

5.3 Shape-based stiction detection for critical valves

Shape-based stiction detection methods were implemented for the critical valves of the board machine on the basic control level. The following fault scenarios were considered for analysis:

- Scenario 1: Stuck pressure control valve in the second drying group.
- Scenario 2: Valve not opening in birch dosing
- Scenario 3: Valve malfunction in the 8th drying group

Based on the available FDD algorithms, the histogram stiction detection method by Horch (2006) and the curve fitting method by He et al (2007) were applied. These methods produce stiction indexes as their diagnosis decision: If the index is high enough, stiction is determined to be present in the valve.

The stiction detection based on histogram shape utilizes filtered second derivative of the process output computed as follows:

$$y_{df}(t) = \left(\frac{(1-\alpha)(1-q^{-1})}{1-\alpha q^{-1}}\right)^2 y(t). \quad (8)$$

The histogram of the signal (8) is computed and it is compared to a Gaussian distribution defined by:

The histogram of the signal (8) is computed and it is compared to a Gaussian distribution defined by:

$$f_G(x) = \frac{1}{\sqrt{2\pi\sigma}} e^{\frac{-(x-\mu)^2}{2\sigma^2}}, \quad (9)$$

and to a camel distribution defined by:

$$f_z(z) = \frac{1}{\sigma\sqrt{2\pi\sigma}} \int_{-A}^{A} \frac{e^{\frac{-(z-x-\mu)^2}{2\sigma^2}}}{\sqrt{A^2-x^2}} dx \quad (10)$$

If normal distribution fits better to the histogram, stiction is detected.

In the curve fitting method, two types of curves are fitted to the measured oscillating signal: sinusoidal curve and triangular curve. A stiction index is then calculated based on the mean squared errors of the fits as follows:

$$SI = \frac{MSE_{sin}}{MSE_{sin}+MSE_{tir}}. \quad (11)$$

To confirm the veracity of the results provided by these methods, stiction detection software (Lee et al 2008) developed by the computer control group in the University of Alberta (UA) was tested parallel. The UA stiction system utilizes a process model identification method to verify and quantify the presence of stiction in a closed-loop system. Table 9 shows the stiction indexes obtained from the fault scenarios.

Table 9 Stiction indexes for the fault scenarios

Fault scenario	Curve fitting stiction index	Histogram Stiction index	UA system
1: Stuck valve	0.8829	1	Stiction
2: Valve not opening	0.6	0	Weak stiction
3: Valve malfunction	0.47	1	Dead-band and stiction

For the fault scenario 1, the stuck pressure valve in the 2nd drying group presents an obvious fault behaviour which can be seen in Figure 8. The control signal increases but the process output remains relatively unaltered. In this scenario both of the tested methods confirm the presence of stiction. The UA stiction system coincides with these results. Figure 9 shows a graph of the values of the stiction index for the curve fitting method, which indicates that stiction is probably present in the valve.

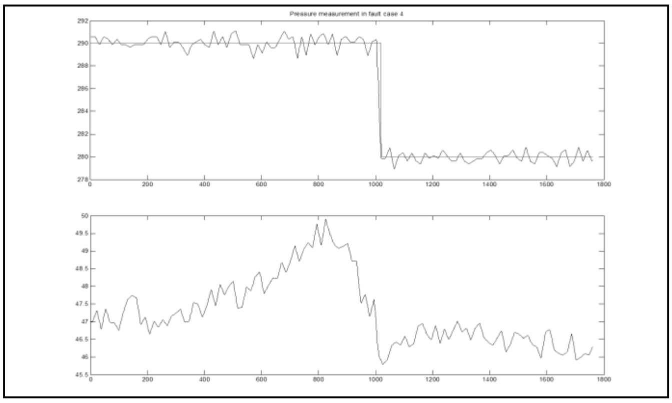

Fig. 8 Pressure measurement and the set point (top panel) and the controller output (bottom) for fault scenario 1

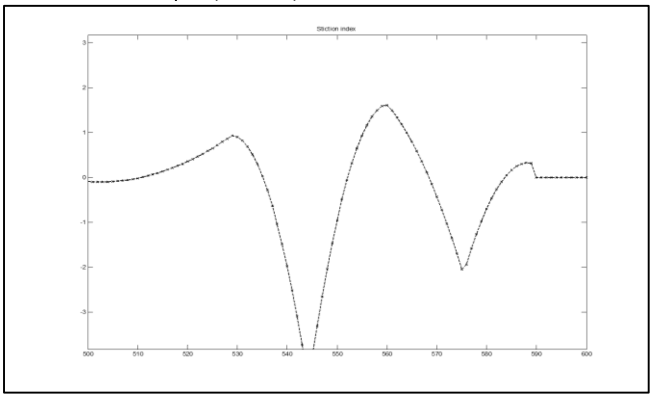

Fig. 9 Stiction index value, the extreme values indicate the presence of stiction

In the fault scenario 2, the flow valve not opening in the birch dosing, the oscillation is clearly present, while the value of the controller output is changing frequently (Figure 10). The curve fitting method and the UA system indicate weak stiction. The histogram method diagnoses a healthy valve.

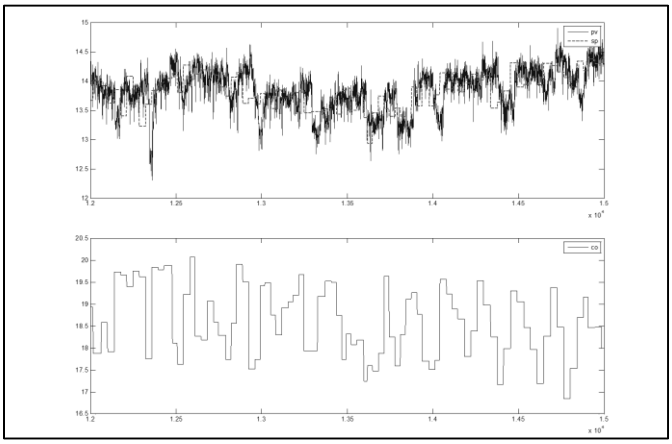

Fig. 10 Flow measurement and the set point (top panel) and Controller output (bottom panel) for the fault scenario 2

The pressure difference valve malfunction in the steam group 8 (fault scenario 3) shows oscillating behaviour, see Figure 11. In this case the UA system and the histogram method diagnose stiction. The curve fitting method is unable to provide a diagnosis decision.

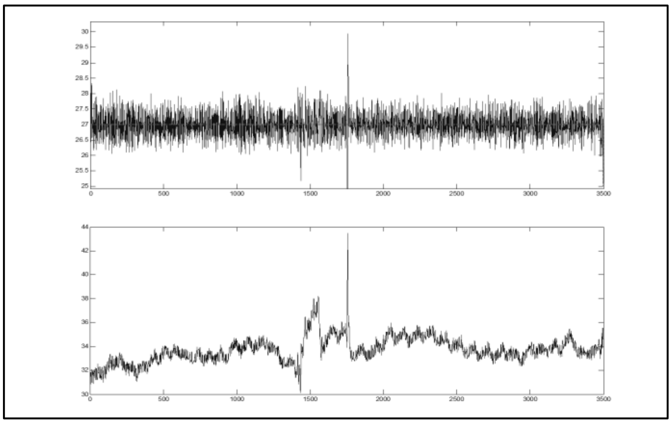

Fig. 11 Pressure difference measurement, the set point (top panel) and the controller output (bottom panel) in fault scenario 3

This study concludes that the histogram method is capable of detecting stiction in most cases. However, in cases where the stiction is weak, the method is unable to provide accurate diagnosis. On the other hand, the curve fitting method is capable of quantifying stiction, making it capable of detecting weak stiction. Nonetheless, the method is susceptible to external disturbances. Therefore, in order to obtain an accurate FDD system, both methods should work in parallel.

Further information on the results and more detailed discussion on this case study can be found in Pozo Garcia et al (2011).

5.4 SISO level - FDD for consistency sensor malfunctions

Detection and diagnosis of consistency sensor malfunctions have been addressed in the earlier study by the authors (Cheng et al 2011), which analysed an FDD system based on the dynamic causal digraph (DCDG) method. The DCDG method is based on multiple process models that describe the causal structure of the process variables in the form of a directed graph or digraph. Each model is used to generate a set of residuals that enables the detection of a fault and the reasoning about its propagation path in the process.

In the same study, an enhanced DCDG method was proposed that improves the fault diagnosis reasoning. The proposed method was used in a case study of the stock preparation and the short circulation sections of a board machine. A causal digraph model was constructed comprising the 30 most important process variables of these sections. The model was used to detect and diagnose the malfunctions of consistency sensors among other fault scenarios. The results showed that the enhanced dynamic causal digraph method was able to provide timely detection and correct diagnosis of consistency sensor faults by taking advantage of the powerful reasoning ability of the method.

6 Conclusions

In this paper, FDD system development for a large-scale board machine has been outlined. One of the main stages in this development was fault analysis. This analysis provided a practical tool and substantial benefits in focusing the FDD development of the large-scale system to the three main focus areas in the process automation hierarchy. At the highest hierarchy level, fouling of the thickness sensor was selected for monitoring due to the important role of that sensor in quality control. At the process unit level, the drying section is one of the key sections of the board machine and therefore the major problems of leakages and blockages in its valves and pipes were selected for FDD development. At the basic control level, valves and consistency sensors were considered as the most important pieces of equipment in this study. In addition to the fault analysis, the paper presented briefly the selection, training, and testing of FDD algorithms and their validation results.

The case study of an industrial board machine confirmed that the fault analysis is well suited for screening the target areas of FDD development. FDD improvement was shown to be necessary in this study at all process hierarchy levels, but the needs can vary in general according to the control level and the process section. More research and industrial large-scale applications are needed to enable specifications of more detailed hierarchical structures of the FDD systems.

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References

ABB A.S (n.d.) EFDD - early fault and disturbance detection, condition monitoring & production optimization. Available from: http://www05.abb.com/global/scot/scot267.nsf/veritydisplay/b16e798c97c2db7d8525771b004c4500/$file/tp004_efdd.pdf. Accessed 25 Oct 2010.

Cheng H, Tikkala VM, Zakharov A, Myller T, Jämsä-Jounela SL (2011) Application of the enhanced dynamic causal digraph method on a three-layer board machine. IEEE Transactions on Control Systems Technology 19(3): 644-655.

Chung H, Bien Z, Park J, Seong P (1994) Incipient multiple fault diagnosis in real time with applications to large-scale systems. IEEE Transactions on Nuclear Science 33(8): 1943-1954

Dash S, Venkatasubramanian V (2000) Challenges in the industrial applications of fault diagnosis systems. Computers & Chemical Engineering 24: 785-791

Ding SX (2008) Model-Based Fault Diagnosis Techinques, 1st edn. Springer-Verlag, Berlin, Germany

Edthofer F, van den Broeke J, Ettl J, Lettl W, Weingartner A (2010) Reliable online water quality monitoring as basis for fault tolerant control. In: Control and Fault Tolerant Systems Nice, France, Oct 6-8, 2010

Gensym Corporation (1997a) G2 Reference Manual Volume 1 Version 5. Gensym Intelligent Real-Time Systems, Cambridge

Gensym Corporation (1997b). Getting Started with G2 Tutorials Version 5. Gensym Intelligent Real-Time Systems, Cambridge

He P, Wang J, Pottmann M, Qin J (2007) A curve fitting method for detecting valve stiction in oscillating control loops. Industrial & Engineerinf Chemistry Research 46: 4549-4560.

Honeywell Inc (2005) Abnormal situation management for industry. Available from: http://statusreports.atp.nist.gov/reports/94-01-0169PDF.pdf. Accessed 2 November 2010

Horch A (2006) Method and a system for evaluation of static friction. United States patent 7047152

Isermann R (2011) Fault-Diagnosis Applications, 1st edn. Springer-Verlag, Berlin, Germany

Jämsä-Jounela SL (2011) Fault diagnosis methods and their applications in the process industry. In: COSY 2011, Special International Conference on Complex Systems: Synergy of Control, Computing & Communications, Ohrid, Macedonia, Sep 16-20, 2011

Kettunen M, Jämsä-Jounela SL (2011) Fault-tolerant model predictive control of a complex industrial dearomatization process. Industrial & Engineering Chemistry Research 50(11): 6755–6768

Kohonen T (2001) Self-Organizing Maps, 3rd edn. Springer-Verlag, Berlin, Germany

Langergraber G, Weingartner A, Fleischmann N (2004) Time-resolved delta spectrometry: a method to define alarm parameters from spectral data. Water Science and Technology 50(11): 13-20.

Langergraber G, van der Broeke J, Lettl W, Weingartner A (2006) Real-time detection of possible harmful events using UV/vis spectrometry. Spectroscopy Europe 18(4): 1-4

Lee G, Yoon E (2001) A Process decomposition strategy for qualitative fault diagnosis of large-scale processes. Industrial & Engineering Chemistry Research 40: 2474-2484

Lee K, Ren Z, Huang B (2008) Novel closed-loop stiction detection and quantification method via system identification. In: ADCONIP Conference, Jasper, Canada, May 4-7, 2008

Lo CH, Wong YK, Rad AB (2004) Model-based fault diagnosis in continuous dynamic systems. ISA Transactions 43: 459-475

Mjaavatten A, Foss BA (1997) A modular system for estimation and diagnosis. Computers & Chemical Engineering 21(11): 1203-1218

Morison D, Foslien W, MacArthur W, Jofriet P (2006) The early event detection toolkit. Available from: http://hpsweb.honeywell.com/NR/rdonlyres/9998BC23-

0175-4937-AA20D86772E52E5B/15009/EarlyEventDetectionToolkitWhitePaper.pdf. Accessed 30 Oct 2010

Power Y, Narozny JA, Barnfield A (2009) Intelligent asset performance management of a uranium solvent extraction circuit. In: IFACMMM 2009, IFAC Workshop on Mining, Mineral and Metal Industry, Vina del Mar, Chile, Oct 14-16, 2009

Pozo Garcia O, Myller T, Kulomaa T, Hämäläinen V, Jämsä-Jounela SL (2011) An application of shape-based stiction detection in critical valves of a board machine. In: 1st Papyrus Workshop on fault diagnosis and fault-tolerant control, Porticcio, France, October 6-7, 2011

Prasad P, Davis J, Jiranpinyo Y, Josephson J, Bhalodia M (1998) Structuring diagnostic knowledge for large-scale process systems. Computers & Chemical Engineering 22(12): 1897-1905

Sourander M, Vermasvuori M, Sauter D, Liikala T, Jämsä-Jounela SL (2008) Fault tolerant control for a dearomatisation process. Journal of Process Control 19(7): 1091-1102

Sundholm P (2000) Mill operations in production of main paper and board grades. In: Paulapuro H. (ed) Papermaking Part 1, Stock Preparation and Wet End, FAPET Oy, pp 12-55

Thornhill NF, Horch A (2007) Advances and new directions in plant-wide disturbance detection and diagnosis. Control Engineering Practice 15: 1196-1206

Tikkala VM, Myller T, Kulomaa T, Hämäläinen V, Jämsä-Jounela SL (2011) Monitoring of caliper sensor fouling in a board machine using self-organizinf maps. Expert Systems with Applications 39(12): 11,228-11,233

Vedam H, Venkatasubramanian V (1999) PCA-SDG based process monitoring and fault diagnosis. Control Engineering Practice 7: 903-917

Venkatasubramanian V (2010) Systemic risks management in complex process plants: Challenges, opportunities and emerging trends. Conference on Control and Fault Tolerant Systems, Nice, France, Oct 6-8, 2010

Venkatasubramanian V, Rengaswamy R., Kavuri SN (2003a) A review of process fault detection and diagnosis, part II: Qualitative models and search strategies. Computers and Chemical Engineering 27: 313-326

Venkatasubramanian V, Rengaswamy R, Kavuri SN, Yin K (2003b) A review of process fault detection and diagnosis, part III: Process history based methods. Computers and Chemical Engineering 27: 327-346

Venkatasubramanian V, Rengaswamy R, Yin K, Kavuri SN (2003c) A review of process fault detection and diagnosis, part I: Quantitative model-based methods. Computers and Chemical Engineering 27: 293-311

Zakharov A (2011) A method for detecting faults or controlling and/or optimizing of an industrial process or a part of it. Finnish Patent Application 20116321 (submitted)